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Forecasting of natural gas consumption with artificial neural networks

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ABSTRACT

In this study, the results of forecasting of the gas demand obtained with the use of artificial neural networks are presented. Design and training of MLP (multilayer perceptron model) was carried out using data describing the actual natural gas consumption in Szczecin (Poland). In the model, calendar (month, day of month, day of week, hour) and weather (temperature) factors, which have a pronounced effect on gas consumption by individual consumers and small industry, were considered. The results of forecasts with the use of MLP models differing in the number of neurons in the hidden layer and in the size of the data set used in the training process were compared. MLP networks with the higher quality were used for the preparation of gas consumption forecast for the additional input data, which was not previously used in the training process. It was found that MLP 22-36-1 model can be successfully used to predict gas consumption on any day of the year and any hour of the day.

1. Introduction

In many countries in Europe (Dilaver et al. [1] and Gutiérrez et al. [2]), Turkey (Erdogdu [3]) or China (Li et al. [4]) a continuous increase in demand for natural gas as a source of energy in the sector of industrial and individual customers can be observed. Due to uneven distribution of natural gas resources in the world, there is a need for gas transmission with the use of pipelines from countries which possess large resources of this raw material, to countries whose economies are dependent on natural gas. Pipeline transport may be considered one of safer and cheaper ways of transport over long distances; however large initial investment are required, which is undertaken when long-term contracts are concluded with the gas supplier. Conclusion of contracts and the development of pipeline infrastructure, however, are based on gas demand forecasts in the subsequent years [5].

Forecast of natural gas demand for a particular city or state is based on anticipation of needs of industrial sector customers, services and households, which are characterized by different characteristics of gas consumption at diurnal, monthly or annual cycle [6]. In the Fig. 1, a fragment of urban gas network is shown, and selected examples of three places of gas consumption by customers of different characteristics of gas consumption during the year are highlighted. Szoplik [7] stated that industrial consumer (type A) consumes the same amount of gas regardless of the season of the year or day. Residential or commercial consumer (type B) consumes gas mainly on heating compartments; therefore it is characterized by daily and seasonal variation over time. However, residential consumer (type C) uses gas only for cooking and therefore, it is characterized by diurnal variations. The variations of gas demand by consumers depending on time of day were analyzed by Szoplik [8].

Variability of gas consumption over time among various groups shows, that gas consumption is dependent on various external factors, thus in prognostic models, different explanatory variables should be considered. Prognostic models may consider calendar- (weekday, daytime, month, season) and weather-related (temperature, humidity, sunshine, wind speed) factors, as well as demographic (general population, number of adults and children in the household, birth rate), economic (Gross Domestic or National Product, the price of gas) factors and the parameters characterizing the building (type of ownership of the building, type of building, size of building area and the degree of glazing, roof type).

These parameters affect gas consumption to a various extent in particular groups of customers. In the group of residential consumers, decrease in air temperature has the greatest impact on the increase in gas consumption, which can be observed in the winter months. However, in the group of industrial consumers, decrease in gas prices and increase in national income have the greatest impact on the increase in gas consumption, which however, largely depend on the state policy.

Acronyms: ANN, artificial neural network; MAPE, mean absolute percentage error; MLP, multilayer perceptron; nRMSE, normalized RMSE; RMSE, root mean square error; R, correlation coefficient; SSE, sum of square error.

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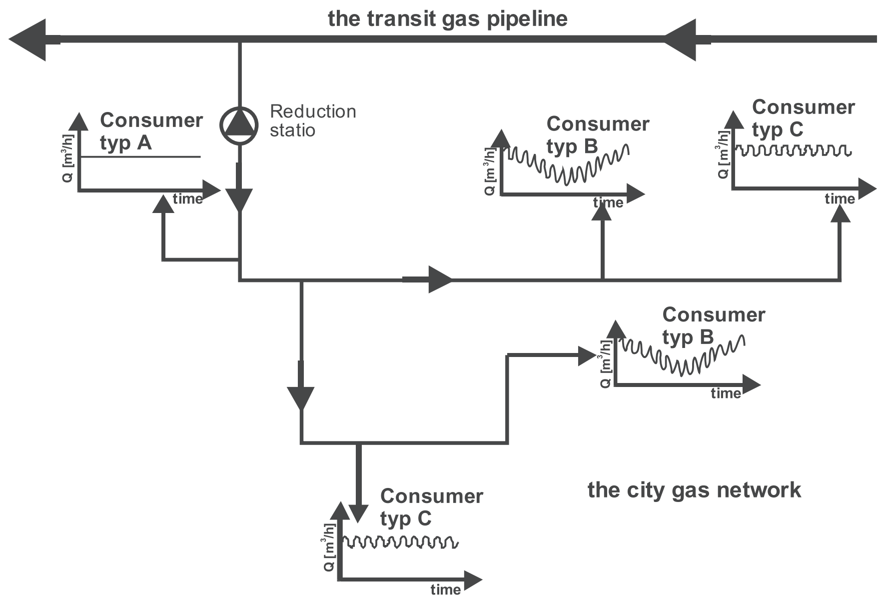

Fig. 1. The fragment of city gas network with depicted objects and gas use characteristics by different groups of consumers.

According to Aydinalp-Koksal and Ugursal [9] and Kavaklioglu et al. [10] when forecasting the energy demand, three groups of models have practical relevance: TS (time series), RM (regression model) or ANN (artificial neural network). In contrast, depending on the type of input data (annual, monthly or hourly) and area, long-term prognosis for the state or short-term for household or city may be developed. The input data for predictive models can be derived from surveys, yearbooks, government studies or forecasts of these factors. The results of forecasts and analyses of energy demand may be presented directly from the model as a relationship or by means of income or price elasticity.

Forecast with the use of TS is based on observations of the same variable collected in the past without the knowledge of the specific relationship between the data. Demirel et al. [11] used AR (auto regressive) and MA (moving average) model with an additional variable (ARMAX) for short-term forecasting of daily gas demand for Istanbul in Turkey pointing that daily temperature followed by first lags of consumption are one of the more important factors in the model. In the model, no impact of the daily national income on the forecast of gas demand was considered. Erdogdu [3] applied the ARIMA model for forecasting monthly or annual gas demand for Turkey, considering factors such as GDP (gross domestic product) and the price of gas in the model. Based on the determined income and price elasticity, it was found that in Turkey the decrease in gas price is not translated directly into increased gas consumption by residents. Akkurt et al. [12] suggested the application of ARIMA model for the annual forecasting and SARIMA model for monthly forecasting of gas demand for Turkey. The effect of temperature and gas prices on the requirement quantity was not considered in the model. Taşpinar et al. [13] used SARIMAX model for short-term forecasting of the daily gas demand for the Sakarya province in Turkey, in which many atmospheric conditions (temperature, cloudiness, humidity and pressure) were considered. SARIMA or SARIMAX methods consider the presence of seasonal factor in time series, hence the quality of the monthly forecasts obtained by these methods is better as compared to the results obtained by ARIMAX method, which provides good results of annual forecasts for gas demand. Śanchez-Úbeda et al. [14] performed medium-term forecasting of industrial end-use natural gas consumption in Spain and proposed novel prediction model based on decomposition approach. Calendar information (day of week, weekends and holidays, Easter and Christmas) as explanatory variables was considered in the model.

The STSM (structural time series model) was used to forecast annual gas demand for Europe [1]. The authors analyzed the impact of various scenarios such as changes in determinants income, natural gas price and the trend of gas consumption in the future, on the size of the forecasted natural gas demand in Europe in 2012–2020, indicating that the variable selection for predictive model specified for a particular country should additionally concern the level of development, prosperity and activity of residents of the state. Potočnik et al. [15] proposed a general approach including a forecasting model, economic incentive model and a risk model to analyze the forecasting error in the context of various influential parameters such as month, day of week or temperature. This model was used in the Slovenian natural gas market.

The largest group consists of RM (regression models) which, depending on the type of relationship between variables, may be linear or non-linear, or may contain one or more explanatory variables. Different scenarios of future changes of variables considered in the model were analyzed. Geem et al. [16] used linear regression or exponential model with four independent variables such as GDP (gross domestic product), population, import and export amounts, for the forecasting of annual gas demand for South Korea. Linear regression model was also used to forecast the annual demand for various energy resources in India [17]. The size of GDP and population were taken into account, no price of gas was considered because gas is consumed mostly by the industry and its price is negotiated individually by each major customer. Linear regression model with three independent variables (GDP per capita, price, temperature) was also used for long-term forecasting of gas demand in Italy [18]. Calculations were conducted for different combinations of each variable value (increase or decrease), and their influence on gas consumption by nonresidential consumers in 2030 was analyzed. Based on income or price elasticity it was estimated, that the air temperature has the greatest impact on the size of the forecasted gas demand, as at average increase of gas price and GDP, the decrease in temperature by 2° results in an increase in gas consumption by up to 10%.

The OLS (ordinary least squares) regression model was used by Demirel et al. [11] and Taşpinar et al. [13] for daily forecast of gas demand in Turkey's cities. Aydinalp-Koksal et al. [9] suggested the application of CDA (conditional demand analysis) model with three components (electricity, natural gas, oil model) and with 45 independent variables, to estimate the national end-use energy consumption in the Canadian residential sector. The degree-day method based on a long-term analysis of past weather reports (mainly temperature) [19] was used to forecast gas demand for a particular building [20] or settlements of buildings [21] in Turkey, or to forecast the demand for energy in household in Uzbekistan [22]. Vondráček et al. [23] proposed a statistical approach (based on nonlinear regression) for the estimation of natural gas consumption of individual residential and small commercial customers.

To forecast gas demand for each of the four sectors of the Chinese economy (primary industry, secondary industry, tertiary industry and residential), Li et al. [4] suggested the use of the system dynamic model with individual set of factors. For long-term forecast, Gutiérrez et al. [2] used stochastic Gompertz innovation diffusion model (SGIDP) to describe the annual gas demand in Spain. In contrast, the logistic curve was used to estimate the demand for gas between 2002 and 2060 in Poland [24] or Iran [25]. The influence of the type of regression function, namely Gompertz, logistic or log-normal [2] was investigated, and in terms of the logistic function, the impact of the method on coefficient determination (NLP or GA) was evaluated [25].

Sabo et al. [26] compared the results of hourly forecasts of gas demand derived from exponential, Gompertz or logistic models, based on natural gas consumption, temperature and temperature forecast data recorded in the past. The authors showed that the best performance of the models is reported for those, for which evident relationship between the gas demand and temperature is observed.

The nonlinear regression model with individual customer effect was used for annual or monthly gas demand forecasting for different target groups in the Czech Republic. The model consisted of temperature-dependent and temperature-independent terms, respectively. Brabec et al. [27] used the nonlinear mixed effects model with individual customer-specific parameters for the forecasting of daily gas demand. The dynamic econometric model with Cobb–Douglas function was used for annual forecasting of gas demand in Bangladesh [28]. The authors analyzed the impact of various scenarios involving national income changes, gas prices, and the size of population, on the future gas consumption in different groups of customers and demonstrated, that the increase in the income of the country is translated into an increase in gas consumption, while the increase in the price or the size of population does not exhibit a significant impact on gas consumption.

ANN (artificial neural network) is a useful tool used to solve complex, especially nonlinear decision problems, optimization, process control, forecast and many others. ANN is based on modeling the action of nerve cells of living organisms and does not require detailed knowledge on the relationship between input and output signals. Artificial intelligence techniques such as neural network or genetic algorithm can be combined together in various ways to form hybrid models offering more flexibility. There are similar examples of such hybrid models in the literature (neural networks and fuzzy systems or genetic algorithm and fuzzy systems).

MLP (multilayer perceptrons), RBF (radial basis function) or FB (feedback network) were the most commonly used in forecasting. The models differed in the number of nods in the network input layer, which was dependent on the number of independent variables considered in the model. Among independent variables represented by the input of the neural network, temperature, gas price, number of customers, time delay (consumption in previous periods), GDP, types of gas customers' needs, design parameters of buildings and furnishings, were the most commonly used. The number of inputs in the ANN differed from 1 to 55. Furthermore, most often the number of neurons in the hidden layer of the network was chosen experimentally. Different functions of neuron activation in the hidden or output layer, as well as various learning algorithms were tested. Demirel et al. [11] applied neural networks and multivariate time series methods to predict short-term natural gas consumption for Turkish company. Comparison of forecasting results acquired from five forecasting models was done based on RMSE, MAD and MAPE (mean absolute percentage error). This comparison showed that ANN model with an error back-propagation algorithm outperformed the other forecasting models. Taspinar et al. [13] proposed a method to short-term natural gas consumption in Sakarya province using MLP (multilayer perceptron), RBF (radial basis function) or time series methods (SARIMAX). The prognostic results demonstrated that time series forecaster for daily prediction of natural gas consumption performs better than MLP or RBF models. Aydinalp-Koksal et al. [9] presented the comparison of neural network (MLP), CDA (conditional demand analysis) and engineering approaches for modeling energy consumption in Canadian residential sector. The study indicated that all three models are capable of accurately predicting end-use energy consumption; however from the perspective of assessing the impact of socio-economic factors, the neural network model outperform CDA and engineering models. In addition, Aydinalp et al. used artificial neural network technique in developing the appliances, lighting and space-cooling energy consumption [29] and for modeling of the space and domestic hot water heating energy consumption in Canadian residential sector [30]. Geem and Roper [16] tested artificial neural network model (MLP) for forecasting the energy demand for South Korea based on several economic indicators (gross domestic product, population, import and export amounts). The comparison of the forecasting results obtained from various models showed that proposed model (feedforward MLP with error back-propagation algorithm) better estimated energy demand than a linear regression or an exponential model in term of root mean squared error. Feedback artificial neural network trained using a hybrid algorithm was applied for short-term electric load prediction in buildings by González and Zamarreño [31]. The prognostic results were excellent but the number of neurons in the hidden layer of ANN, the optimal size of data window and parameters of training algorithm were not analyzed. Voyant et al., in papers [32] and [33], successfully applied artificial neural networks to forecast hourly or daily solar global radiation. Voyant et al. [32] used a hybrid model MLP/ARMA to forecast hourly global radiation that outperformed classical models. Voyant et al. in paper [33] analyzed the influence of the use of endogenous and exogenous variables with ANN (multivariate method) on the quality of prediction of daily solar radiation.

Khotanzad [34] studied the idea of combination of a two-stage forecasting system for prediction of daily natural gas consumption. The first stage included a multilayer feedforward neural network and nonlinear function in the input, which in the second stage models are mixed. Authors used eight different (linear or nonlinear) combination modules to mix. The results showed that combination strategies based on a single neural network outperform other approaches. Liu et al. [35] analyzed the use of different prognostic models (single or multiple neural networks without preprocessing method of multiwavelet transform and combination forecasting model of multiwavelet transform and multiple neural networks) for power short-term load forecasting. The simulation results showed that accuracy of the combination based on a multiple neural network model and multiwavelet transform was higher than any one single network model or the combination forecast model including three neural networks. Potočnik et al. [36] involved various types of forecasting models: benchmark model include random walk and temperature correlation, linear models include stepwise regression method and auto regressive model with exogenous input and nonlinear models include neural network models and support vector regression. The models were tested in their static and adaptive versions and were applied to two natural consumption systems on different scales. For applications in daily natural gas consumption forecasting the adaptive linear model was recommended. Combinational approach based on improved neural network with backpropagation algorithm and optimized genetic algorithm were used for short-term gas load forecasting by Yu et al. [37]. Proposed model provided more satisfactory prediction accuracy and relatively small iteration number. Kovačič & Šarler [38] compared the differences between actually supplied quantities determined by natural gas supplier and predicted by classical statistical or genetic programming model. The results revealed that the genetic programming model performs approximately two times more favorably.

The fuzzy logic model incorporated with meteorological effect was used to improve load predictions of the power system in Jordan [39]. The results showed that error was less than 5% for forecasting based on fuzzy logic compared to results for conventional statistical forecasting method.

Kazemi et al. [40] used a hybrid intelligent approach called genetic-based adaptive neuro-fuzzy inference system to model, estimate, analyze and control short-term fluctuations of electrical loads.

Proposed model provides better estimation with respect to other models such as genetic algorithm, neural network or decision tree. Kodogiannis et al. [41] employed a novel clustering-based fuzzy wavelet neural network model for short-term electric load forecasting. Their results showed that the proposed load forecasting model providing predictions significantly outperformed previous approach based on neural network models.

Betancourt-Torcat et al. [42] proposed Mixed Integer Nonlinear Optimization Programming Model for forecasting the Canadian Oil Sands energy demands and total energy cost of operations for 2020 for three different production scenarios. Moreover, the Integrated Energy Optimization Model for Oil Sands operations presented in Ref. [43] was used to perform sensitivity analyses on CO_2 reduction level and natural gas price. Charry-Sanchez et al. [44] proposed upgraders' energy optimization model as a practical tool to study the Oil Sands operations for the year 2035 for different natural gas prices and under operational and environmental constrains. A stochastic mixed-integer nonlinear optimization model was developed by Gomes et al. [45] to specify optimal upgraders' infrastructure that is expected to be required for Oil Sands to satisfy the projected production demands at minimum cost under uncertainty in key economic and operational parameters. The uncertain parameters in the model can be implemented using Gaussian, log-normal or exponential probability distribution function.

Kovačič and Šarler [38] studied forecasting with the use of genetic algorithm to optimize the plan of gas procurement in the steel plant in Slovenia. In this case, Štore Steel Company was a customer of gas, for which monthly plan of production was known and demanding for gas was reported in a weekly cycle with a division into each day of the week, separately. After the end of each month, comparison of actual and ordered gas consumption was made. If the actual gas consumption was higher than the forecasted in the weekly plan, then for each day the steel plant was charged financial penalties.

In this case, it was a weekly forecast with the accuracy of one day. However, depending on the country and the type of the consumer, different approaches in the development of the procurement plan of various energy resources are used. In Poland, there is an annual ordering system of gas with an accuracy of 1 m^3/h. The size of the ordered hourly gas stream is similar and obligates in a given calendar year. Industrial customer or operator of the pipeline are responsible for the development of gas demand forecast. On the other hand, use over the ordered gas stream by the industrial consumer or by a total number of residential customers in a country even by 1 m^3 per hour results in a very high penalty charges for the customer.

Knowing the structure of the customers in the city and the influence of selected external factors on the consumption of gas, it is possible using the proposed neural network model to forecast hourly peak offtake of gas in the following year for which procurement plan of hourly demand for gas will be developed. The model was developed for the network operator to forecast the peak gas offtakes from the network and to reduce the financial losses resulting from deal failure.

The objective of this paper was to develop ANN models (MultiLayer Perceptrons) to forecast hourly natural gas consumption in residential and commercial sector in Szczecin in Poland. In this city, natural gas is mainly used for space heating, water heating and cooking. MLP model consisted of five independent variables such as: temperature, month, day of month, day of week, hour of the day. To train the neural network and for model validation, real weather and calendar data, data on gas consumption in the city between 1st January 2009 and 31st December 2011 was used. These data were supported by the operator of the pipeline as part of cooperation between the Department of natural gas in Szczecin and the Department of Chemical Engineering. In the future, MLP model may be used in emergency situations for the estimation of gas consumption in the city depending on temperature and time. In addition, the ANN model in parallel with the risk model, may be used to develop a short-term plan of gas demand for Szczecin.

2. Variability of gas consumption in Szczecin and selection of variables for model build

The number of gas customers in Szczecin between 2009 and 2011 was around 132 thousand. The gas was primarily consumed for space, water heating and cooking. The total gas consumed by all customers was recorded by devices installed on three reducing stations, supplying gas network in the city. The selection of explanatory variables included in the model was preceded by the analysis of the impact of various factors on the actual gas consumption in the city. The total gas consumption by residential and commercial consumers and the average ambient temperature in Szczecin in the following hours between 1st January 2009 and 31st December 2011 were presented in the Figs. 2–5. It was found, that the gas consumption in Szczecin varies depending on the month (Fig. 2) and depends on the temperature (Figs. 2 and 3) hour of the day, day of the week (Fig. 4) and day of the month (Fig. 5).

Low air temperatures in winter months cause significantly increased gas consumption in these months, because the gas is mainly used for space and water heating (Fig. 3). In the winter season, increased gas consumption was observed during daylight hours in comparison to the night, which results from the type of consumers' needs (water and space heating during daylight hours). Moreover, gas consumption depends on the day of the week or the day of the month (holidays, public holidays). On holidays (Saturday and Sunday) morning peak of gas consumption was observed in later hours as compared to the working days (Fig. 4). In contrast, the gas consumption prior the holidays is significantly higher as compared to the gas consumption reported on holidays or working days (Fig. 5). Variability of gas consumption in seasonal and diurnal

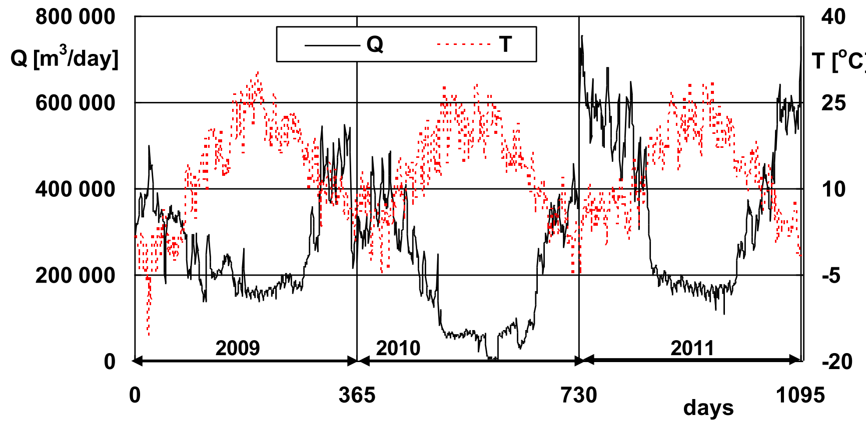

Fig. 2. Variation of the gas consumption Q in days in 2009, 2010 and 2011; T – ambient temperature [°C], Q – volumetric gas flow [m^3/day].

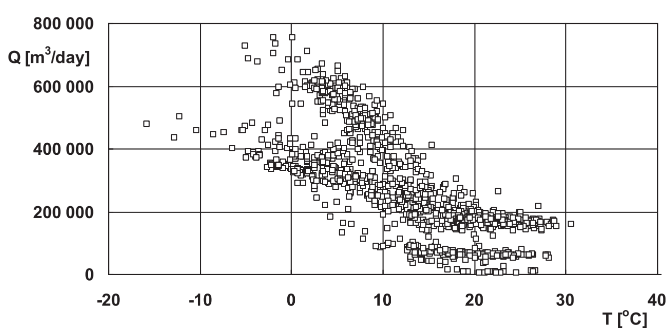

Fig. 3. Relationship between gas demand and ambient temperature, data for 2009–2011.

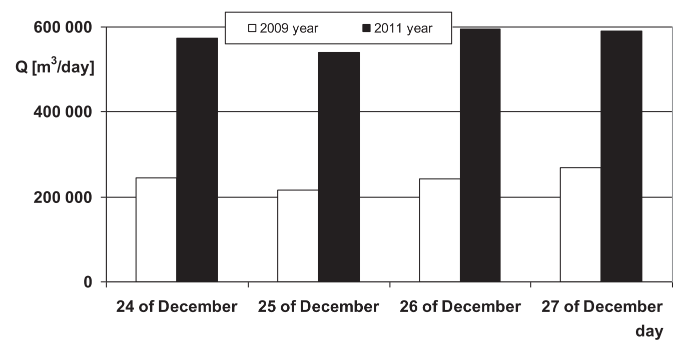

Fig. 5. Variation of daily gas consumption Q between selected four days; 24th and 27th December – working days; 25th and 26th December – holidays.

cycle is obviously dependent on the air temperature, exhibits repeatable character in successive years and can be forecasted.

In the developed ANN model, no weather factors other than ambient temperature (e.g. sunlight, humidity, wind speed), which can have an impact on gas consumption, will be taken into account. Additionally, no reliable data characteristic for the whole city was available. Moreover, one decided not to introduce any economic factors (price of gas, GDP per capita) into the model, as it was proved, that they have no significant impact on the outcome of the short-term forecast.

3. The multilayer perceptrons

ANN (artificial neural network) is an example of the statistical model, whose structure and function are based on the operation of the human brain. Artificial neurons also called Processing Element, in which computational processes are performed are the counterpart of natural neurons in the brain. The model of an artificial neuron was shown in Fig. 6. The artificial neural network consists of multiple of artificial neurons arranged in layers and joined together in different ways.

MultiLayer Perceptrons MLP networks (also known as multilayer feed-forward networks) are the most popular and most widely used models of ANNs in many practical applications. A typical network diagram presented in Fig. 7 is a full-connected, three layer, feed-forward, perceptron neural network. Fully connected means that the output signal from each input and hidden neuron is distributed to all of the neurons in the successive layer. The MLP network consists of an input layer and an output layer, but the number of hidden layers may vary. The number of neurons in the input layer of the network is equal to the number of independent variables (a seven-day week, 12 months, temperature, hour, day of the month), while the number of neurons in the output layer

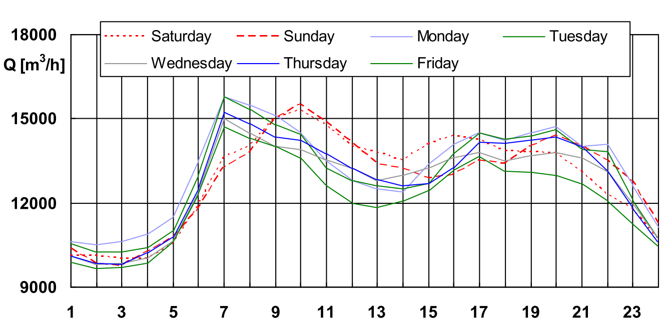

Fig. 4. Variation of hourly gas consumption Q during seven days selected in 2011.

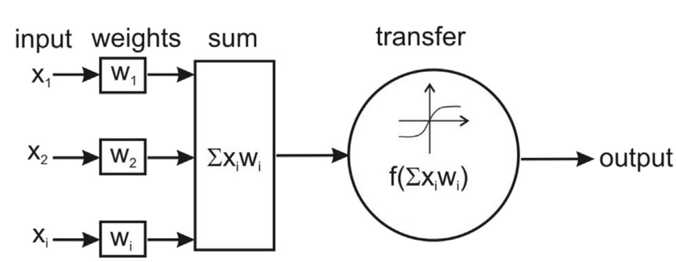

Fig. 6. The neuron model in a hidden or output layer of the artificial neuron network.

is equal to the number of dependent variables (quantity of gas demand).

The topology of the MLP network presented in Fig. 7 has only three layers (one – input, one – output and one hidden layer). The beginning of a neural network operation, presented in Fig. 7 is emerging signals at the network input, carrying new tasks to solve. The signals from input layer x_i are sent to all neurons of the hidden layer Y. Each neuron of the hidden layer possesses defined number of inputs, and with each input a given w_i^X weight is connected. Inside neurons' hidden layer, based on the information from input layer x_i and weights w_i^X, aggregate input value which is the sum of weighted inputs $\Sigma x_i w_i^X$ is calculated. In contrast, activation functions of neurons enable to determine the output values of neurons in the hidden layer y_i. Then, the signals from all neurons located in the hidden layer are distributed to all of the neurons of the output layer. In the neurons of the output layer, similarly as in neurons from the hidden layer, firstly aggregation of the weighted inputs to a neuron followed by the activation of the output signal occurs. In all the neurons of the hidden and output layers, two processes are carried out: aggregation of the input signals and activation of the output signal (Fig. 6).

In the studies, different activation functions of neurons were tested and the best were selected. For neurons from the hidden layer, hyperbolic tangent function (Eq. (1)) was applied, and for neurons from the output layer, exponential function (Eq. (2)) was used.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

$$g(x) = e^x \tag{2}$$

The weights of neurons from the hidden w_i^X and output w_j^Y layers were determined in the process of network learning based on BFGS (broyden-fletcher-goldfarb-shanno) technique.

Entire training process was repeated until initial values from the network as compared to real values, were obtained. Network error (SSE (sum of square error)) was calculated as the aggregated measure of differences between initial real values (d_i) and values calculated with the use of network (z_i).

$$SSE = \sum_{i=1}^{N} (d_i - z_i)^2 \tag{3}$$

Reliability of a neural network was evaluated based on the value of calculated correlation coefficient R ($Q\ exp$, $Q\ MLP$ – actual and forecasted gas consumption, N – data number).

$$R = \frac{N\sum(Q\ \exp\cdot QMLP) - \sum Q\ \exp \sum QMLP}{\sqrt{\left[N\sum(Q\ \exp)^2 - (\sum Q\ \exp)^2\right]}\cdot\sqrt{\left[N\sum(QMLP)^2 - (\sum QMLP)^2\right]}} \tag{4}$$

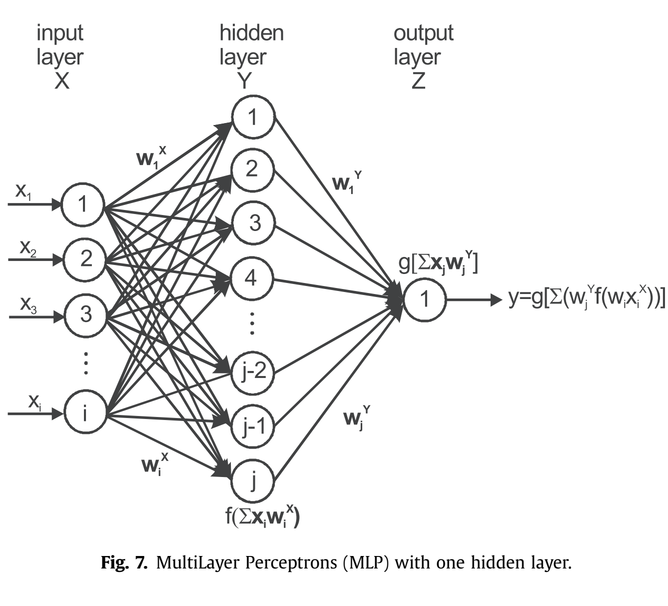

Fig. 7. MultiLayer Perceptrons (MLP) with one hidden layer.

4. Methodology

Development and training of MLP network was carried out using actual gas consumption in the city as well as calendar and weather factors. Historical data describing the actual hourly consumption of gas during the period from 1st January 2009 to 31st December 2011 was provided by the network operator, while the weather data were read from the meteorological database. Based on the analysis of the impact of various factors on the gas consumption in the city, one identified five factors which were taken into account in the input layer of ANN (temperature, hour of day, day of week, month, day of month). Thus, the number of explanatory variables in the MLP model was 22 (7 days a week, 12 months, temperature, hour of day, day of month).

The input data set was divided into three subsets. The first one sized 8760 (set 1) included data for 2009, the second one sized 17520 (set 2) included data for 2009 and 2010. In the process of MLP training, in each of the subsets, training, test and validation sets were randomly drawn. The training set which accounted for 70% of a particular data matrix, was used for the modification of the weight of neurons from input and hidden layers. The test set comprising 20% of the data were used for actual monitoring of the learning process. The remaining 10% constituted validation set used to assess the quality of the network after completion of the learning process. Additionally, the third subset sized 8760 (set 3) included data for 2011 and was not used in the training of MLP network. This subset however, was used to assess the forecast ability of the best MLP network trained on set 1 and set 2. Development and training of MLP network was carried out in Statistica Automated Neural Network 8.0 separately for each subset of input data (set 1 or set 2), changing the number of neurons in the hidden layer of the network between the range of 5 and 40, and the format of the activation function of neurons from hidden and output layers. The division of the input data into a subset of set 1 and set 2 aimed at testing how the multiplicity of the set used in the process of training of the neural network affects the network structure and the quality of the forecast. Furthermore, the use of two data sets allowed the selection of two independent networks with the same number of neurons in the hidden layer, which differed in the value of correlation coefficient, and two networks with the same value of correlation coefficient but differing in the number of neurons in the hidden layer.

Table 1
Summary of correlation coefficients, R, and SSE errors for MLP networks with different structure.

	MLP	R_L	R_T	R_V	SSE_L	SSE_T	SSE_V
Set 1	22-5-1	0.937	0.930	0.928	0.197	0.224	0.233
	22-10-1	0.968	0.969	0.964	0.102	0.103	0.119
	22-15-1	0.982	0.983	0.977	0.056	0.056	0.075
	22-20-1	0.988	0.989	0.986	0.037	0.038	0.047
	22-25-1	0.992	0.992	0.990	0.025	0.027	0.033
	22-28-1	0.992	0.991	0.989	0.027	0.031	0.037
	22-35-1	0.992	0.990	0.988	0.026	0.033	0.039
	22-40-1	0.991	0.990	0.987	0.028	0.033	0.043
Set 2	22-5-1	0.878	0.872	0.877	0.361	0.380	0.341
	22-10-1	0.924	0.921	0.920	0.229	0.241	0.227
	22-15-1	0.919	0.915	0.910	0.244	0.260	0.255
	22-20-1	0.953	0.953	0.951	0.145	0.145	0.146
	22-25-1	0.958	0.955	0.949	0.130	0.141	0.148
	22-28-1	0.958	0.951	0.951	0.133	0.152	0.140
	22-36-1	0.988	0.985	0.984	0.040	0.046	0.048
	22-40-1	0.989	0.987	0.986	0.035	0.040	0.038

In the Table 1, parameters characterizing quality (R) and SSE (sum of squares error) for networks differed with the number of neurons in the hidden layer, were summarized. These parameters were determined based on Eqs (3) and (4) separately for the data from the training (L), test (T) and validation (V) sets. Regardless of the data size used in the learning process (set 1 or set 2), an increase in the number of neurons in the hidden layer of MLP network influences reduction of the network error and increase in the correlation coefficient. If the number of neurons in the hidden layer of the network is identical, the correlation coefficients R_L, R_T, R_V are comparable, as SSE_L, SSE_T, SSE_V values. In contrast, there are clear differences between the values of the correlation coefficient (R) and SSE error for network with the same number of neurons in the hidden layer, but trained on subsets of different size (set 1 and set 2).

For instance, one compared the correlation coefficients and errors for MLP 22-25-1 (set 1) and MLP 22-25-1 (set 2) networks and it was found, that the error for the trained network on more abundant data set is almost three-fold higher. Comparison of the results presented in Table 1 showed that the use of subsets of different size, particularly set 1 or set 2 to train the network with the same structure, causes that for the networks trained on a set of lower multiplicity, higher correlation coefficients are obtained for a network of lower number of neurons in the hidden layer in comparison to network for which larger data sets were used in the training process.

Among eight MLP networks trained on each data set, the best was selected, that is the one that was characterized by the highest correlation coefficient R and the smallest value of SSE. For networks trained on a set 1, MLP 22-25-1 network was selected, and among networks trained on a set 2, MLP 22-36-1 network was selected. Additionally, among networks trained on the set 2, MLP 22-25-1 was also selected for further studies.

5. Results and discussion

Comparison of the actual (Q exp) and forecasted gas consumption with the use of network Q (MLP 22-25-1, set 1) is presented in Fig. 8. In the figure, the results for only a subset of the test set obtained for a standard winter month (1.01.2009–31.01.2009) and for the hypothetical summer month (1.07.2009–31.07.2009) were presented. By contrast, in Fig. 9, a similar comparison was presented, however for the results obtained with the use of network composed of 36 neurons in the hidden layer and trained on set 2. In the case of the data and the results included in the test set, better accordance of actual and forecasted gas consumption is observed in the summer months, when the gas consumption is lower in comparison to the winter months. In addition, analysis of the data from Figs. 8 and 9 showed higher accordance between actual and forecasted data obtained with the use of MLP 22-25-1 (set 1) in comparison to the actual and forecasted data obtained by MLP network 22-36-1 (set 2).

Detailed comparison between actual and forecasted gas consumption with the use of MLP networks in the following hours of the day of hypothetical day of January or July 2009 is illustrated in Fig. 10 and Fig. 11. Slightly higher accordance of actual and forecasted gas consumption was achieved for MLP 22-25-1 trained on the set 1 in comparison to MLP 22-36-1 trained on the set 2.

The quality of the forecasts obtained using MLP 22-25-1 (set 1) and MLP 22-36-1 (set 2) networks was evaluated based on the values of errors: MAPE, RMSE and nRMSE (normalized RMSE). The mean absolute percentage error (MAPE) was calculated according to the formula:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Q\ exp - QMLP}{Q\ exp}\right| \cdot 100\% \tag{5}$$

The root mean square error RMSE and its normalized value nRMSE were determined from the formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q\ exp - QMLP)^2} \tag{6}$$

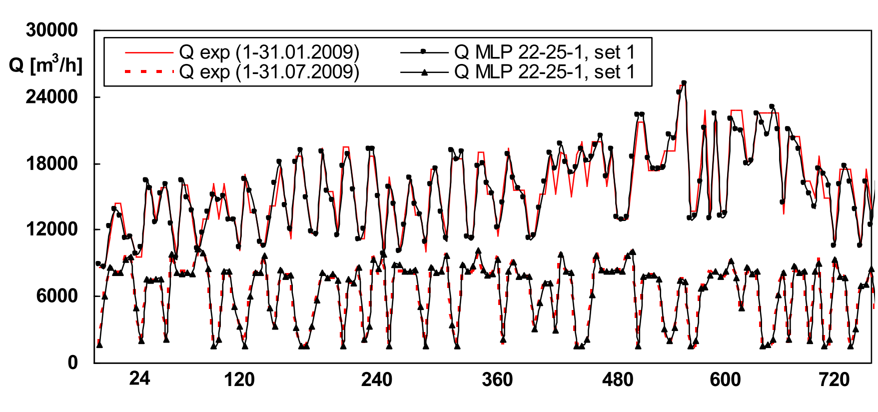

Fig. 8. Comparison between actual (Q exp) and forecasted demand for gas with the use of Q MLP 22-25-1 (test set 1) network.

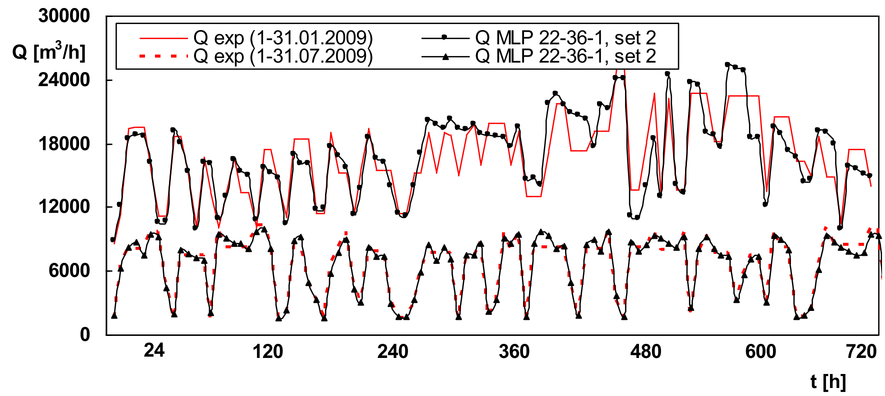

Fig. 9. Comparison between actual (Q exp) and forecasted demand for gas with the use of Q MLP 22-36-1 (test set 2) network.

$$nRMSE = \frac{RMSE}{Q\ \exp_{(max)} - Q\ \exp_{(min)}} \tag{7}$$

In Table 2, summary of values of the forecast errors, particularly MAPE, RMSE and nRMSE determined for subsequent months of 2009 for MLP 22-25-1 (set 1) and MLP 22-36-1 (set 2) networks, was presented. One can observe that higher values of MAPE are more characteristic for MLP 22-36-1 (set 2) network than for MLP 22-25-1 (set 1) network. Furthermore, comparison of MAPE for different months of the year showed that lower values of MAPE are characteristic for the winter months (XI, XII, I, II, III). Lower values of the relative error MAPE characterize forecasts with better performance, which means that in the winter months, differences between the actual and the forecasted values were lower than in the other months, and additionally the demand for gas in those months is higher, which significantly contributed to obtain the smaller value of the relative error MAPE.

On the other hand, regardless of the MLP network type, the highest value of RMSE is observed for data recorded for November, and the highest nRMSE value is characteristic for January and February. RMSE error shows the average size of the forecast error obtained from the MLP model. Higher values of RMSE error observed in the month from the beginning of the winter season were caused by the occurrence of greater differences between the actual and the forecasted values as a result of neural network analysis. While smaller variation of actual gas demand observed in the peak of the winter season caused that maximum values of nRMSE were reported for these months. Forecasts characterized by better performance are those for which the estimated values of MAPE, RMSE and nRMSE are the smallest.

5.1. Application of MLP network

The trained neural networks, particularly MLP 22-25-1 (set 1), MLP 22-36-1 (set 2) and additionally MLP 22-25-1 (set 2), were then used for the preparation of the gas demand forecast for Szczecin for the actual weather and calendar data, characteristic for 2011 (set 3). This data were not previously used during the learning process of any network. The results of the forecasts were then verified with actual data of gas consumption in Szczecin in 2011.

The results of the forecasts for gas demand for the city reported with the use of MLP 22-25-1 and 22-36-1 MLP trained on sets of different size (set 1 or set 2) are illustrated in Fig. 12. In Fig. 12a one presented the results in the form of actual (Q exp) gas consumption in the following hours in January 2011, and the volume of gas streams forecasted by the neural network composed of 25 or 36 neurons in the hidden layer (Q MLP) and trained on set 1 or set 2. Analogous results, however, illustrating the comparison between actual and forecasted results for July 2011, are presented in Fig. 12b. In terms of hourly forecast prepared for the winter month (Fig. 12a) (low air temperature, high gas streams), one can observe clear differences between the amounts of actual and forecasted gas

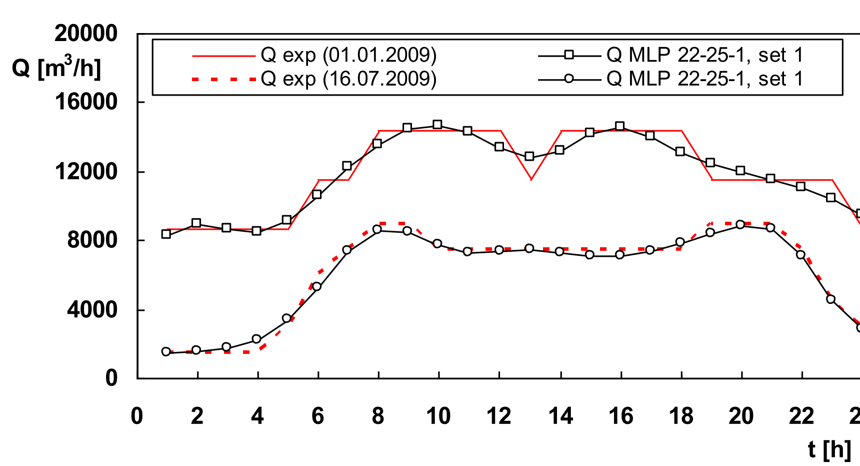

Fig. 10. Comparison between actual (Q exp) and forecasted (Q MLP) gas consumption by MLP 22-25-1 network trained on the set 1, data for exemplary day of the winter season (01.01.2009) or the summer season (16.07.2009).

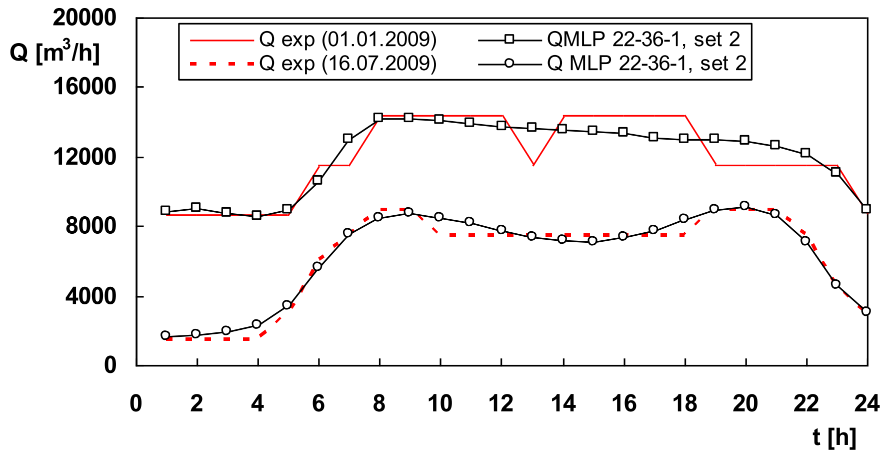

Fig. 11. Comparison between actual (Q exp) and forecasted (Q MLP) gas consumption by MLP 22-25-1 network trained on the set 2, data for exemplary day of the winter season (01.01.2009) or the summer season (16.07.2009).

consumption by MLP 22-25-1 (set 1) network, and good agreement of actual and forecasted data was obtained for MLP 22-25-1 (set 2) and MLP 22-36-1 (set 2) networks.

In contrast, clearly higher accordance between actual and forecasted data were found when the forecasted demand for gas characteristic for the summer months, was lower (high air temperature associated with low gas consumption) (Fig. 12b). In this case, regardless of the MLP network structure, the actual (Q exp) and the forecasted gas consumption with the use of the network (MLP Q), are comparable. A detailed comparison between actual and forecasted gas consumption by residents of Szczecin in the following hours of the day with the use of three types of MLP networks on hypothetical January 2 and August 7 2011 was presented in Fig. 13.

It can be observed that for the preparation of an hourly forecast of gas consumption in the winter season (Fig. 13a), when gas streams are higher in comparison to the summer, MLP 22-25-1 (set 1) network is unable to correctly forecast the size of the gas stream for other input data than that used during the learning process. In contrast, hourly forecasts of gas consumption are correct during the summer days (Fig. 13b), for which demand for gas is observed. However, no correlation between the quality of forecasts and the hour of the day was reported. Application of MLP network, regardless of the structure and the data used in the learning process can correctly reflect the daily variation in gas consumption in the city.

MAPE, RMSE and nRMSE calculated for gas consumption forecasts in Szczecin, with the use of MLP 22-25-1 (trained on set 1 and set 2) and MLP 22-36-1 (trained on the set 2) networks, for the subsequent months of 2011, were provided in Table 3. Comparison of the quality of forecasts showed, that the highest values of MAPE characterize 22-25-1 MLP network trained on the set 1. Additionally, MAPE values for forecasts obtained from MLP 22-25-1 and MLP 22-36-1 trained on the set 2, are similar. The lowest values of RMSE and nRMSE of gas consumption forecasts in 2011 characterize summer months (V, VI, VII and VIII). However, the errors of forecasts for MLP 22-25-1 (set 1) are several times higher in comparison to the remaining two, tested in the analyses of MLP networks. Additionally, in the winter months (from October to April), the forecasted demand for gas may be even twice lower than the actual values. The existence of such large differences between the actual data and data obtained with the use of MLP 22-25-1 (set 1) in the winter months, can be explained by different average ambient temperatures during the winter in 2009 and 2011. MPL 22-25-1 network (set 1) was trained on a data set equal to 8760, which included gas consumption registered only in 2009, when the average air temperature in January 2009 was (-5 °C), while the average temperature in analogous period in 2011 was ($+3$ °C). Based on the data presented in Table 3, it can be assumed that the quality of the prepared forecast is more influenced by the size of the data used in the learning process than the structure of the network, for instance, higher number of neurons in the hidden layer.

Comparison of the forecasts results with the use of QMLP network and the actual demand for gas in 2011 is illustrated in Fig. 14. MLP 22-25-1 MLP (set 1 and set 2) and MLP 22-36-1 (set 2) differed in both, the number of neurons in the hidden layer of the network, as well as the size of the data used in the learning process and the value of SSE during learning process. The highest error of learning (SSE = 13%) corresponded to MLP 22-25-1 (set 2), while the lowest error of learning (SSE = 3%) corresponded to MLP 22-25-1 (set 1) network. However, if the MLP networks were used to prepare the forecast of gas demand for the input data different than that used in the learning process, one observed that MLP 22-25-1 or 22-36-1 MLP networks trained on a larger data set (set 2) have better ability to correctly forecast the demand for gas with the time horizon of 1 h, in comparison to MLP 22-25-1 network trained on the set 1.

Table 2
Comparison of MAPE, RMSE and nRMSE for monthly data.

Month	MLP 22-25-1 (set 1)			MLP 22-36-1 (set 2)		
	MAPE [%]	RMSE	nRMSE	MAPE [%]	RMSE	nRMSE
I	5.0	963.0	0.0587	7.1	1493.3	0.0910
II	4.8	819.3	0.0582	7.6	1285.7	0.0913
III	6.3	901.9	0.0532	6.4	1002.0	0.0591
IV	6.3	666.1	0.0443	10.8	1140.4	0.0759
V	6.0	454.8	0.0289	8.9	814.7	0.0517
VI	6.8	462.4	0.0325	7.9	644.3	0.0452
VII	6.2	341.0	0.0379	9.5	547.6	0.0608
VIII	6.1	370.0	0.0349	9.8	732.7	0.0692
IX	5.4	515.4	0.0576	8.8	861.5	0.0963
X	5.6	761.2	0.0383	8.0	1145.2	0.0576
XI	5.5	1209.6	0.0475	7.3	1710.6	0.0672
XII	5.0	1059.6	0.0508	6.7	1410.0	0.0676

6. Conclusions

The objective of the discussed and presented results of the study was to obtain forecasts of the cumulative gas demand for residents

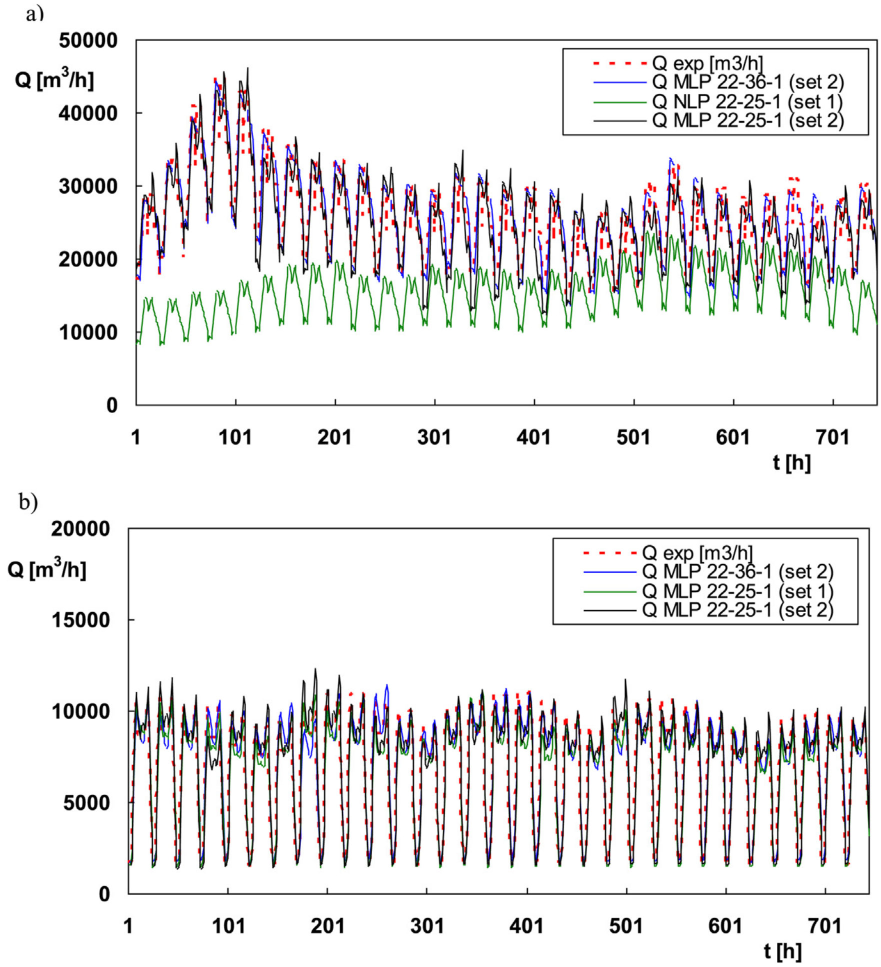

Fig. 12. Comparison between actual and forecasted hourly demand for gas (Qexp) with the use of Q MLP 22-36-1 (set 2), MLP 22-25-1 (set 2) or MLP 22-25-1 (set 1) networks; a) results for January 2011; b) results for July 2011.

of Szczecin. Based on the obtained forecast results, it was found that application of MLP 22-36-1 neural network trained on a set of data representing the actual gas consumption in the city between 1st January 2009 and 31st December 2010 enables to obtain the forecast with the average MAPE = 8%. Lower values of MAPE are observed in the winter months, because at that time, gas consumption in the city is higher in comparison to the summer. Random sampling of the training, test and validation set was used in this study, which allowed to avoid selection bias of the data used in the process of neural network training.

Taking into account, that in Szczecin gas is mainly consumed by individual consumers, who are unpredictable to some extent (change of residence, unplanned winter vacation, change of energy supplier), it can be concluded that the forecast accuracy obtained is acceptable. The proposed model of MLP network takes into account the impact of calendar and weather (day of month, day of week, month, time, and temperature) factors on the amount of gas demand in the city for any day of the year or hour of the day. The selection of variables introduced to the model was preceded by an experimental analysis of the impact of various factors on the demand for gas in the city, and in the model presented in the study, only those factors that have a significant impact on gas consumption were included. Weather factors other than temperature (sunshine, wind), although may affect the actual gas consumption especially in the winter, were not included in the MLP model due to inability of their correct estimation for the entire city.

The proposed model of MLP 22-36-1 network can be successfully used to forecast the hourly demand for gas in the city for any day of the week or month, depending on the hour of the day and the ambient temperature. Neural network design and selection of the number of neurons in the hidden layer were based on real data provided by the gas network operator in the city. Apart from the time-consuming process of preparing the input data and training of a neural network, forecasting using MLP model is simple, and the results are satisfactory. Moreover, once trained the neural network can be used repeatedly with no additional expense. Therefore model used, choice of the independent variables and obtained results have no equivalent in the open literature.

Maximum monthly MAPE forecasting error of gas demand estimated for the input data different than that used in the process of MLP 22-36-1 network training, is estimated at 9% (except for one summer month with extremely low gas consumption). Based on the results of forecasts and acceptable threshold of forecast error, in particular 9%, one attempted to assess the cumulative risk of erroneous forecast. Risk model developed consists of 5 groups of factors taken into account at the entrance of the MLP model (month, day of month, day of week, hour and temperature). Preliminary studies on the modeling of erroneous forecast risk showed that among the factors taken into account in the model, the time and the temperature exert the greatest impact on the forecast error. The risk will be presented as a probability of the forecast error greater than 9%.

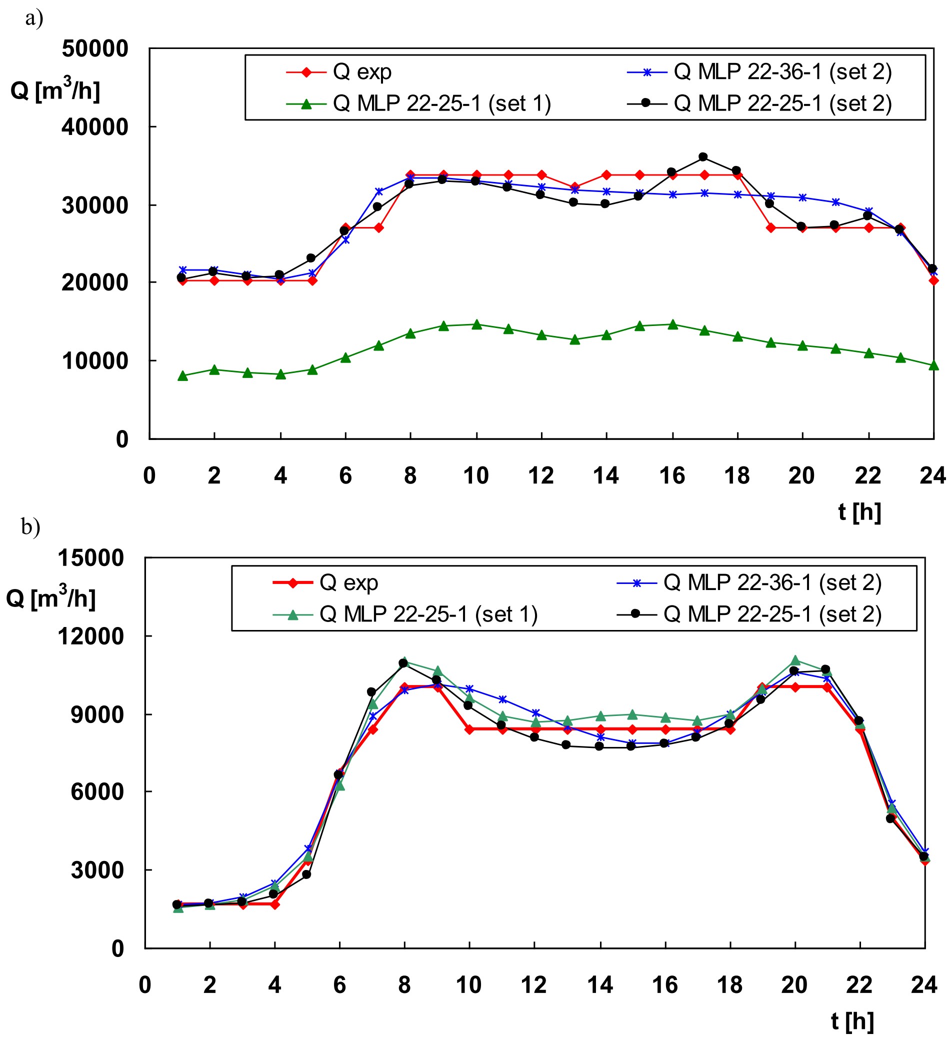

Fig. 13. Comparison between actual and forecasted hourly demand for gas (Qexp) with the use of MLP 22-36-1 (set 2), MLP 22-25-1 (set 2) or MLP 22-25-1 (set 1); a) results for 2.01.2011, b) results for 8.07.2011.

However, MLP 22-36-1 network model developed and complemented with the model of risk of erroneous forecast will be tested in practice in the future while forecasting gas stream ordered by the network operator.

The proposed MLP model of the neural network was trained using the real data on gas consumption in the city and includes the impact of selected calendar and weather factors on the quantity of gas demand by customers living in Szczecin. MLP neural network model of a similar structure, after training will have an application towards cities of similar structure of customers living in similar climatic zone and of similar level of wealth, economic development and political system of the state.

Table 3
Comparison of MAPE, RMSE and nRMSE values for the following months in 2011.

Month	MLP 22-25-1 (set 1)			MLP 22-25-1 (set 2)			MLP 22-36-1 (set 2)		
	MAPE	RMSE	nRMSE	MAPE	RMSE	nRMSE	MAPE	RMSE	nRMSE
I	39.7	12181.6	0.413	8.0	2624.6	0.089	6.4	2166.6	0.073
II	38.9	10503.3	0.520	12.0	4194.8	0.208	5.5	1640.9	0.081
III	44.3	11064.8	0.361	14.1	4317.9	0.141	5.5	1544.0	0.050
IV	42.5	8322.7	0.309	14.7	2907.4	0.108	7.8	1617.9	0.060
V	15.3	1733.9	0.148	10.2	724.8	0.062	9.3	729.9	0.062
VI	21.1	1958.5	0.189	10.5	834.7	0.080	8.9	644.5	0.062
VII	7.9	592.7	0.062	7.2	569.9	0.059	8.9	582.2	0.060
VIII	12.7	992.6	0.104	13.2	819.1	0.086	11.0	760.4	0.080
IX	20.1	2485.4	0.173	11.7	1290.0	0.090	8.0	918.7	0.064
X	22.0	4137.5	0.185	8.2	1416.6	0.064	7.8	1408.1	0.063
XI	19.9	4989.7	0.156	8.2	1877.5	0.059	7.2	1836.4	0.057
XII	30.9	9718.7	0.465	6.7	2119.1	0.101	5.6	1738.8	0.083

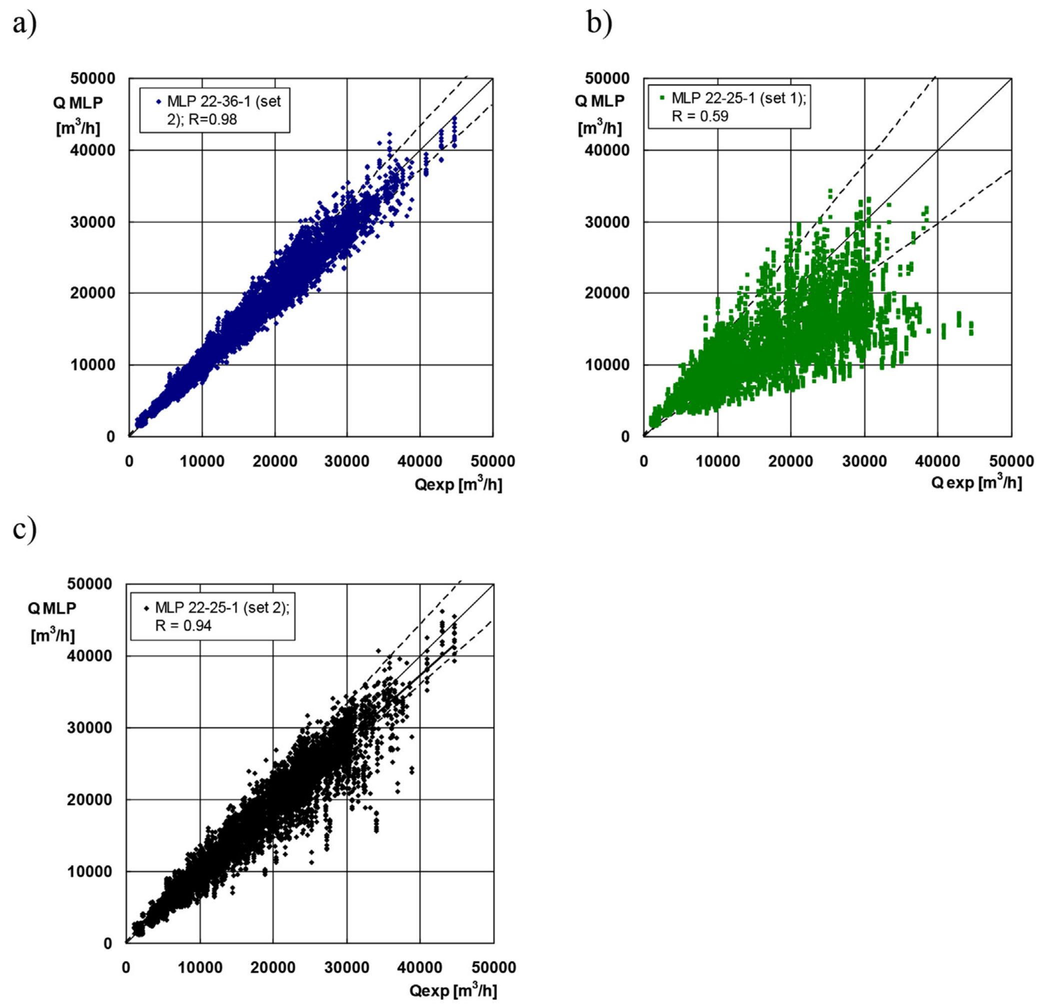

Fig. 14. Comparison between actual (Qexp) and forecasted (QMLP) demand for gas for the data from 2011, (set 3); a) MLP 22-36-1, set 2, SSE = 4.5%, mean MAPE 8%; b) MLP 22-25-1, set 1, SSE = 3.2%, mean MAPE 26%; c) MLP 22-25-1; set 2, SSE = 13%, mean MAPE = 10%.

However, it can be assumed that the development of a model for another city or state should always be preceded by the analysis assessing the impact of various factors on gas demand in order to optimize the selection of variables in the model, depending on the intended purpose of forecasting and the accepted forecast horizon. In addition, depending on the accuracy, performance and availability of the input data, the model should be appropriately chosen and the acceptable level of accuracy of the forecast should be established.

Based on the analysis of literature data, it has been found that the forecasting methods based on artificial neural network models surpass the traditional models of time series and regression models in terms of the performance of the forecasts. The operation of the artificial neural network is modeled on the action of the human nervous system, thus forecasting of gas demand without the knowledge of the specific relationships between variables and without knowledge on their impact on the forecasted value is possible. In addition, ANN models can be used in any situation (for short-term, long-term forecasting, for trend series, series characterized by daily or seasonal variability). However, it can be assumed that hybrid models more and more often used in the forecasting, combining various techniques of artificial intelligence, e.g.: artificial neural network models, genetic algorithm or fuzzy logic will enable the development of forecasts with higher performance than artificial neural network models.

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References

[1] Dilaver Ö, Dilaver Z, Hunt LC. What drives natural gas consumption in Europe? Analysis and projections. J Nat Gas Sci Eng 2014;19:125–36.
[2] Gutiérrez R, Nafidi A, Gutiérrez Sánchez R. Forecasting total natural-gas consumption in Spain by using stochastic Gompertz innovation diffusion model. Appl Energy 2005;80:115–24.
[3] Erdogdu E. Natural gas demand in Turkey. Appl Energy 2010;87:211–9.
[4] Li J, Dong X, Shangguan J, Hook M. Forecasting the growth of China's natural gas consumption. Energy 2011;36:1380–5.
[5] Soldo B. Forecasting natural gas consumption. Appl Energy 2012;92:26–37.
[6] Tavakoli E, Montazerin N. Stochastic analysis of natural gas consumption in residential and commercial buildings. Energy Build 2011;43:2289–97.
[7] Szoplik J. The Gas transportation in a pipeline network. In: Hamid Al-Megren Dr, editor. Advances in natural gas technology. InTech; 2012, ISBN 978-953-51-0507-7. http://dx.doi.org/10.5772/36902. Available from: http://www.intechopen.com/books/advances-in-natural-gas-technology/the-gas-transportation-in-a-pipeline-network.
[8] Szoplik J. The steady-state simulations for gas flow in a pipeline network. Chem Eng Trans 2010;21:1459–64.

[9] Aydinalp-Koksal M, Ugursal VI. Comparison of neural network, conditional demand analysis, and engineering approaches for modeling end-use energy consumption in the residential sector. Appl Energy 2008;85: 271–96.
[10] Kavaklioglu K, Ceylan H, Oztirk HK, Canyurt OE. Modeling and prediction of Turkey's electricity consumption using artificial neural network. Energy Convers Manag 2009;50:2719–27.
[11] Demirel ÖP, Zaim S, Çalişkan A, Özuyar P. Forecasting natural gas consumption in Istambul using neural networks and multivariate time series methods. Turk J Elec Eng Comp Sci 2012;20(5):695–711.
[12] Akkurt M, Demirel OF, Zaim S. Forecasting Turkey's natural gas consumption by using time series methods. Eur J Econ Political Stud 2010;2:1–21.
[13] Taşpinar F, Çelebi N, Tutkun N. Forecasting of daily natural gas consumption on regional basis in Turkey using various computational methods. Energy Build 2013;56:23–31.
[14] Sánchez-Úbeda EF, Berzosa A. Modeling and forecasting industrial end-use natural gas consumption. Energy Econ 2007;29:710–42.
[15] Potočnik P, Thaler M, Govekar E, Grabec I, Poredoš A. Forecasting risks of natural gas consumption in Slovenia. Energy Policy 2007;35:4271–82.
[16] Geem ZW, Roper WE. Energy demand estimation of South Korea using artificial neural network. Energy Policy 2009;37:4049–54.
[17] Parikh J, Purohit P, Maitra P. Demand projections of petroleum products and natural gas in India. Energy 2007;32:1825–37.
[18] Bianco V, Scarpa F, Tagliafico LA. Scenario analysis of nonresidential natural gas consumption in Italy. Appl Energy 2014;113:392–403.
[19] Satman A, Yalcinkaya N. Heating and cooling degree-hours for Turkey. Energy 1999;24:833–40.
[20] Sarak H, Satman A. The degree-day method to estimate the residential heating natural gas consumption in Turkey: a case study. Energy 2003;28:929–39.
[21] Durmayaz A, Kadioğlu M, Şen Z. An application of the degree-hours method to estimate the residential heating energy requirement and fuel consumption in Istanbul. Energy 2000;25:1245–56.
[22] Kenisarin M, Kenisarina K. Energy saving potential in the residential sector of Uzbekistan. Energy 2007:1319–25.
[23] Vondráček J, Pelikán E, Konár O, Čermáková J, Eben K, Malý M, et al. A statistical model for the estimation of natural gas consumption. Appl Energy 2008;85:362–70.
[24] Siemek J, Nagy S, Rychlicki S. Estimation of natural-gas consumption in Poland based on the logistic-curve interpretation. Appl Energy 2003;75:1–7.
[25] Forouzanfar M, Doustmohammadsi A, Menhaj MB, Hasanzadeh S. Modeling and estimation of the natural gas consumption for residential and commercial sector in Iran. Appl Energy 2010;87:268–74.
[26] Sabo K, Scitovski R, Vazler I, Zekić-Sušac M. Mathematical models of natural gas consumption. Energy Convers Manag 2011;52:1721–7.
[27] Brabec M, Konár O, Pelikán E, Malý M. A nonlinear mixed effects model for the prediction of natural gas consumption by individual customers. Int J Forecast 2008;24:659–78.
[28] Wadud Z, Dey HS, Kabir MdA, Khan SI. Modeling and forecasting natural gas demand in Bangladesh. Energy Policy 2011;39:7372–80.
[29] Aydinalp M, Ugursal VI, Fung AS. Modeling of the appliance, lighting, and space-cooling energy consumption in the residential sector using neural networks. Appl Energy 2002;71:87–110.
[30] Aydinalp M, Ugursal VI, Fung AS. Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks. Appl Energy 2004;79:159–78.
[31] González PA, Zamarreño JM. Prediction of hourly energy consumption in buildings based on a feedback artificial neural network. Energy Build 2005;37: 595–601.
[32] Voyant C, Muselli M, Paoli Ch, Nivet ML. Numerical weather prediction (NWP) and hybrid ARMA/ANN model to predict global radiation. Energy 2012;39: 341–55.
[33] Voyant C, Muselli M, Paoli Ch, Novet ML. Optimization of an artificial neural network dedicated to the multivariate forecasting of daily global radiation. Energy 2011;36:348–59.
[34] Khotanzad A. Combination of artificial neural-network forecasters for prediction of natural gas consumption. IEEE Trans Neural Netw 2000;11(2): 464–73.
[35] Liu Z, Li W, Sun W. A novel method of short-term load forecasting based on multiwavelet transform and multiple neural networks. Neural Comput Applic 2013;22:271–7.
[36] Potočnik P, Soldo B, Šimunović G, Šarić T, Jeromen A. Comparison of static and adaptive models for short-term residential natural gas forecasting in Croatia. Appl Energy 2014;129:94–103.
[37] Yu F, Xu X. A short-term load forecasting model of natural gas based on optimized genetic algorithm and improved BP neural network. Appl Energy 2014;134:102–13.
[38] Kovačič M, Šarler B. Genetic programming prediction of natural gas consumption in a steel plant. Energy 2014;66:273–84.
[39] Mamlook R, Badran O, Abdulhadi E. A fuzzy inference model for short-term load forecasting. Energy Policy 2009;37:1239–48.
[40] Kazemi SMR, Hoseini MMS, Abbasian-Naghneh S, Rahmati SHA. An evolutionary-based adaptive neuro-fuzzy inference system for intelligent short-term load forecasting. Int Trans Operational Res 2014;21:311–26.
[41] Kodogiannis VS, Amina M, Petrounias I. A clustering-based fuzzy wavelet neural network model for short-term load forecasting. Int J Neural Syst 2013;23(5):1350024.
[42] Betancourt-Torcat A, Gutierrez G, Elkamel A, Ricardez-Sandoval L. Integrated energy optimization model for oil sands operations. Industrial Eng Chem Res 2011;50:12641–63.
[43] Betancourt-Torcat A, Elkamel A, Ricardez-Sandoval L. A modeling study of the effect of carbon dioxide mitigation strategies, natural gas price and steam consumption on the Canadian oil sands operations. Energy 2012;45:1018–33.
[44] Charry-Sanchez J, Betancourt-Torcat A, Ricardez-Sandoval L. An optimization energy model for the upgrading processes of Canadian unconventional oil. Energy 2014;68:629–43.
[45] Gomes U, Patil B, Betancourt-Torcat A, Ricardez-Sandoval L. Optimal infrastructure of the upgrading operations in the oil sands under uncertainty: a multiscenario MINLP approach. Industrial Eng Chem Res 2014;53:16406–24.